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Abstract:

The aim of this paper is to verify whether school resource factors have an impact on the quality of education. This latter is measured with the help of a unique database on student scores in international skills tests. The general difficulties inherent in this type of study are the possibility of endogeneity bias and measurement errors. After estimation bias correction, we show that improvement in the quality of educational systems does not necessarily require an increase in school resources. When an alternative indicator of the performance of educational systems is used, our results are confirmed. Consequently, one should remain cautious about recommending purely financial measures to improve quality of education.

Key words: Quality of education, School performance, School resources.

J.E.L. Classification: H5, I2, O4

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1. Introduction

The majority of countries throughout the world devote between 1% and 11% of their GDP to education; equally often, this item of expenditure accounts for one fifth of government spending. Given the rapid growth and large magnitude of education spending, governments have been increasingly interested in ways of controlling education costs. One possible strategy is to modify the institutional structure of the educational system in order to improve the quality of education. There is a lack of clear consensus on whether the quality of an educational system can be improved simply by increasing educational expenditure. More generally, school resource factors as a whole do not appear to explain school performance in any satisfactory manner. In one of the very first studies in this field, Coleman *et al*. (1966) found very weak effects of school resources on student performance. Their report was very influential, giving rise to several hundred articles seeking to measure the impact of school resource variables on student performance. Effects such as class size, the level of educational expenditure and teachers' pay were tested.

Recent exchanges between Eric Hanushek and Alan Krueger underline the lack of consensus about the validity of a relation between educational inputs (such as spending) and the output of the system, often measured by students' scores in skills tests. For example, Hanushek (1998) and Krueger (1998, 2000) analyze the panel data on educational expenditure and the results of NAEP tests (National Assessment of Educational Progress) in the United States. The NAEP is a survey of American students' acquired skills in reading, writing, mathematics and science. From his analysis, Krueger concludes that the increase in spending has led to a slight increase in students' scores, whereas Hanushek finds no clear and robust relation between school resources and student performance.

The aim of this paper is to test the extent to which school resource factors influence educational performance. This latter is measured by the quality of education, itself estimated on the basis of international surveys on student skills. The aim is to calculate an educational production function (EPF) in which an output (the quality of education) is related to certain inputs (school resource factors). Although many studies have estimated the relation between educational inputs and student test scores, these studies are most often based on microeconomic analyses. International comparisons are rare, due to the lack of comparable and homogeneous data. Below, we describe the most influential studies in this field.

Two major studies (Hanushek and Kimko, 2000; Lee and Barro, 2001) have been conducted into the relation between educational variables and test results, using aggregate data. Hanushek and Kimko (2000) construct an international database of student test scores for a sample of 39 countries (for the complete methodology, see Hanushek and Kim, 1995). To test for the existence of an educational production function, the authors regress the measurements of educational performance with input indicators. They emphasize that the conventional measurements of education (such as class size at primary level, government spending per student or the share of GDP allocated to educational expenditure) have no significant effect on the results achieved in the international tests.

Lee and Barro (2001) look for the determinants of school quality in a panel database that includes measurements of education inputs and outputs for a larger number of countries. The authors take into account the results in mathematics, science and reading for students of different ages, in the same surveys as those used by Hanushek and Kimko (2000), for several years from 1964 and 1991. To the contrary of Hanushek and Kimko (2000), they show that school resources, including teachers' pay, have a significant impact on the skills tests, while class size have a significant negative effect on test scores.

Other works have performed the same type of estimation. Al Samarrai (2002) presents a review of the literature together with further results. Without testing survey data, Gupta, Verhoeven and Tiongson (1999) show the need to differentiate between countries according to their economic level in the estimation of the educational production function. Finally, Hanushek and Luque (2003) carry the analyses of Hanushek and Kimko (2000) further. More complete reviews of the literature can be found in Leclercq (2005) and Al Samarrai (2002).

In itself, we do not take into account, in this paper, the dimension relating to the organization of educational systems or the internal workings of the “black box” that they constitute. Our viewpoint is from a macroeconomic level, centered rather on the concept of educational production function. The objective here is to assess the extent to which school resource factors do or do not affect levels of school performance.

Nevertheless, compared with previous works, this paper proposes several advances. Firstly, we take into account two different indicators for the measurement of educational performance, where most of the studies limit themselves to one. Using two complementary measurements gives us the possibility of verifying the validity of our results. Further, our comparative international study adopts a panel perspective, enabling us to control for unobservable fixed effects. In fact, most of the previous studies do not control for bias due to omitted variables and fixed effects. Because we have panel data, we can take into account all the invariant effects whose characteristics are specific to the countries’ educational systems. Another advantage of the panel database is that it enables us to take into account the possible endogeneity of school resource factors. To our knowledge, no other macroeconomic study uses regressors to purge endogeneity bias. Yet it seems fairly logical to imagine that a double relation of causality might exist between resource factors and the performance of educational systems. For example, an educational system may perform well because classes are small in size. In parallel, because of its high performance, the government may opt for a voluntary reduction in class size. Other examples can be found, and they all underline the need to take into account the bias generated by this possible endogeneity. That is we set out to do in this paper.

The rest of the paper is structured as follows. In section 2, we describe the methodology used to construct our data on the quality of education (which we call the "qualitative indicators of human capital" or QIHC) and the other input indicators. Section 3 presents the modelling and the main results obtained. Section 4 concludes.

2. Data and methodology

2.1. Database relative to the quality of education

The data used to measure the quality of education comes from the international surveys on educational achievement. Since 1964, international tests are administered to students from different countries in order to evaluate their level on mathematics, science and other skills. These qualitative indicators of human capital (QIHC) can be considered an alternative to the strictly quantitative variables of education, such as school enrollment. The studies by Hanushek and Kimko (2000) and Lee and Barro (2001) have already adopted such an approach.

Strictly speaking, the aim is to *quantify*, on a scale of 1 to 100, the *quality* of education, or more precisely the scores of representative samples of students from different countries in international achievement tests. We take into account 6 groups of international surveys into student achievement. Our data have been taken from Lee and Barro (2001) for the surveys prior to 1995 and from the official reports for the other surveys (see table 2 for a presentation of the surveys). Below, we present the general methodology. For a more detailed presentation, see Altinok and Murseli (2007) and Altinok (2009)[2].

[2] The database used in this paper is the same of the one which can be found in Altinok and Murseli (2007). The updated database presented in Altinok (2009) is slightly different. Please see Altinok (2009) for the differences between the two databases.

We have used the most recent results from 6 different groups of international surveys (IEA, PISA, SACMEQ, PASEC, LLECE and MLA[3]). For the meaning of all these initials, see the note to Table 2. Previous analyses have used surveys from the period 1961 to 1990, without considering the question of their quality. Lee and Barro (2001), for example, took the scores for all the tests available between these two dates, for all the skills tested, without any readjustment. Hanushek and Kimko (2000) took into account the quality of the data, to a certain extent, by weighting the gross results by standard errors. But they re-calibrated the data solely on the basis of the American NAEP survey (National Assessment of Educational Progress). The authors assumed that the results from this survey were sufficient for overall anchoring of the data. In addition, they did not take into account the results of surveys conducted after 1990. Yet most international surveys actually started after this date. Widening the analysis to cover all the available surveys can, in particular, help us to confirm or disprove the results of previous studies.

The database is in the form of a panel, covering the period 1964-2005. We compile the results from all the surveys measuring student achievements at primary and secondary level. We have two groups of surveys: those in which the United States took part (series A), where we can anchor the data to a specific survey (NAEP), and those in which the United States did not take part (series B), where we anchor the data on countries that have taken part in several different surveys. The anchoring we use in series A, on the American NAEP survey, is the same as that used by Hanushek and Kimko (2000). The NAEP has been the principal tool for measuring student achievements in the United States since 1969. The IAEP is the international equivalent of the NAEP. Thus, the procedure of evaluation is based on American curricula. At different periods since 1970, American students aged 9, 13 and 17 have been

[3] For the meaning of all these initials, see the note to Table 2.

tested on their achievements in science and mathematics. These tests provide an absolute measurement of reference for the level of achievements in the United States. In order to collect the data from both the IEA and the IAEP surveys at the same time, Hanushek and Kimko (2000) used the American results as "references". Thus, they modified the means of the IEA surveys to make them equal to the nearest means in the IEAP surveys (for age, school year and skill tested). Unlike Hanushek and Kimko, in order to obtain indicators comparable to those obtained in series B, we have not re-weighted the scores by the measurement errors. For series B – the surveys in which the United States did not take part – we have adopted the methodology of anchoring. This consists in evaluating the level of difficulty of the different tests based on the results of countries that have taken part in several different surveys. For example, if country *x* performs better in test A than in test B, with the two tests taking place at about the same date, then we can assume that test A is easier than test B, and a readjustment proportional to the difficulty is therefore necessary. In the end, we obtain 42 series of tests for all age groups (9, 10, 13, 14, 15). As a next step, given that certain series concern the same year and the same level of schooling (primary or secondary), grouping these together brings the final number of test series down to 26.

In this study, we use the scores in mathematics, because this is a skill that is easier to compare between countries than reading or science. Furthermore, we use the standardized tests for secondary education, because this is probably the most appropriate educational level for measuring the quality of education. This is also the level for which we have the most observations. It should be noted that our sample is relatively small and unbalanced, because not all the countries took part in all the surveys. Nevertheless, it does enable us to perform econometric analyses that can confirm or disprove previous studies. In addition, to make up for the lack of data and to be able to compare results, we use another educational output (the net enrolment rate at secondary education, see below).

2.2. Database relative to school factors and alternative output measure

As well as the qualitative variables on education constructed and described above, we have also used a set of input variables, to estimate the school production function. For the data from the period 1960-1990, these are drawn mainly from the database of Barro and Lee (1996). The following variables are considered: teacher pay at primary school level as a percentage of GDP per capita (variable *SHSALP*), class size at primary and secondary school level (variables *TEAPRI* and *TEASEC* respectively), government spending on education per student as a percentage of GDP per capita (variables *SHPUPP* and *SHPUPS*, for primary and secondary levels respectively) and repetition rates (*REPPRI* and *REPSEC*). As these data are only available up until 1990, we have updated them by drawing mainly on data from UNESCO and the World Bank (see UNESCO, 2004, 2005, 2007 and World Bank, 2002, 2007). As regards the variable *SHSALP*, we have estimated it using data available from UNESCO and then completed the missing data from the World Bank (2002). We have calculated teachers' pay as a percentage of GDP per capita by dividing the total amount paid to teachers over one year by the number of teachers employed during the year in question. The variable *SHSALP* is then obtained by expressing this as a fraction of GDP per capita. The variables of government spending on education per student have been updated using data extracted from the UNESCO Institute for Statistics: these are expressed as percentages of GDP per capita, for primary and secondary school levels separately.

The variable concerning the average number of years in education for those aged 25 or over (variable *ADEDU*) has been drawn from Barro and Lee (2001). In their study, Lee and Barro (2001) preferred to use the average number of years spent by adults in primary school education, without giving any specific justification. They even pointed out that they had not included the average number of years spent in secondary education because the variable was not significant. Consequently, we prefer to use the number of years spent in school by adults without distinguishing between the levels of education, for there are no grounds for not including the years spend in secondary education and above. As the sample of countries available in the database of Barro and Lee (2001) is fairly small, we have predicted the variable *ADEDU* from the school life expectancy (expressed in years), available in the UNESCO databases (see UNESCO, 2004 and 2005). These two variables are closely linked by a lag effect: as a general rule, the school life expectancy for youngsters is higher than that for adults, for the first variable takes into account evolutions in the school enrollment of the young.

Indicators of educational inequalities have been drawn from Altinok (2007). These indicators cover several dimensions of inequality in education by grouping together Gini index scores and other forms of inequality (notably gender inequalities and drop-out school rate). See Altinok (2007) for a presentation of the methodology. The values of the index range from 0 to 100; the higher the value, the higher the level of inequalities. The data are available for the period 1960-2000, with intervals of 5 years between each observation.

To compare the results, we use a second indicator of educational expenditure: spending on education as a percentage of GDP. Although it is impossible for us to distinguish between each level of education, this indicator can serve as an alternative to the above measurements. The data are drawn from UNESCO and are available for the period 1970-2005. The sources of the data are indicated in Table 1. In addition, elements of descriptive statistics are presented in Table 3.

2.3. Drawbacks relative to the qualitative indicators of human capital

Although the methodology used was designed to measure level of equivalence between the different surveys, it has its limits. Three such limits are discussed below, although there may be others.

The first concerns the anchoring of data to scores obtained in the United States of America. When gauging the difficulty of a particular survey, its data are adjusted to the score of the United States of America both in the survey and in the NAEP. This implies that the NAEP is a sound benchmark for measuring the performance in the United States of America. Yet the published NAEP findings may include a measure of distortion, which could in turn lead to distortion when adjusting the survey concerned. Nevertheless, the anchoring of data on a separate source is the only known procedure for the optimal calibration of surveys in relation to each other. Ideally, data on learning achievement since the mid-1960s should be available for another country, but only the United States of America is believed to have compiled such data at the time. Moreover, to avoid adjustments reliant on the NAEP only, an anchoring methodology is used which consists of an identical linear conversion for surveys administered by the same body (the "general NAEP anchoring methodology").

Furthermore, the nature of the skills assessed may differ from survey to survey, in which case the surveys may not be readily comparable. While some surveys (such as the IEA surveys) tend to measure learning achievement in terms of knowledge, others (such as the OECD surveys) focus more on the level of pupils' skills. In this particular case, any equivalence established may be distorted, as the "products" of education measured in this way are not clearly equivalent. Despite this difference in the kind of "acquisition" measured, the surveys arguably yield a sound assessment of pupils' attainment in mathematics, science and reading.

Finally, as the adjustments are based on scores obtained by the United States of America, irrespective of the methodology used, the database cannot include surveys in which the United States of America has not taken part, such as regional SACMEQ, PASEC, LLECE and MLA surveys. Another methodology that would include regional surveys have been used, but it has its own drawbacks.

3. Model and results

In this section, we estimate the educational production function. We start by presenting the general model. The following subsection describes the econometric techniques used to correct estimation bias. Finally, we discuss the results of the estimations.

3.1. The model

We estimate the educational production function using qualitative indicators of human capital (*QIHC*) and the net enrollment ratio at secondary school level. The educational production function includes both input and output indicators.

Two different variables are used for educational output, including the scores in student skill tests (*QIHC*). In order to compare our results with the classic indicator of education quality, a second indicator is used. The net enrollment ratio at secondary level (*NERSEC*) can be considered as a measure of the performance of an educational system. Clearly, this cannot be treated as a formal indicator of student performance; nevertheless, if a large proportion of students succeed in leaving the secondary level without either dropping-out or repeating years, we can assume that the good performance of the educational system is at least partly responsible. Family factors are represented by a proxy variable of parents' education. This is measured by the number of years spent at school by adults aged 25 and over (*ADEDU*). It should be noted that this variable can also measure the education level of the teachers. There are four variables relating to school resources. The first concerns government spending on education. This is measured on the basis of each country's effort, not in absolute terms: we therefore use a variable measuring educational expenditure per student for each educational level as a percentage of GDP per capita (*SHPUPP* and *SHPUPS* for primary and secondary schools respectively). However, as Lee and Barro (2001) observe, as private spending is not taken into account by these variables, there may be important errors of measurement. To verify the validity of our results, we also use the indicator of educational expenditure as a percentage of GNP (*EXPGNP*). Unfortunately, this indicator reflects the whole of educational expenditure, not the spending on particular levels. Teachers' pay is also measured in relation to GDP per capita (*SHSALP*). Class size represents another resource factor (*TEAPRI* and *TEASEC* for the primary and secondary levels respectively). Unlike Lee and Barro (2001), we include the repetition rates as an input indicator, because we believe it has more to do with a choice of educational policy than a question of educational efficiency (*REPPRI* and *REPSEC* for the primary and secondary levels respectively). Lastly, it is also possible to consider the level of educational inequalities as a lever of economic policy. A country may quite deliberately choose to favour selective access to a given level of education and so accentuate inequalities in schooling. For that reason, we include the indicators of educational inequalities (*INEDU*) in the estimation.

It is important to note that the panel is unbalanced and the number of observations varies considerably depending on the estimations. For example, less than 200 observations are available with the indicators of educational quality in mathematics at the secondary level. Using the net enrollment rate for secondary education provides about 370 observations. We now move on to discuss the regression methods used.

3.2. Regression methods used

We employ several econometric techniques to estimate the educational production function. We start by using the ordinary least squares (OLS) estimator, introducing dummies for the different years in order to capture intrinsic temporal variations. As we cannot, in this case, use the whole database of test scores, we restrict it to the indicators of the quality of schooling in mathematics. The model is written as follows:

$$q_{it} = \alpha_{it} + \beta_1 f_{it-1} + \beta_2 s_{it-1} + \mu_t + v_{it} \tag{1}$$

where q denotes educational output, f denotes family factors, s covers all the school resource variables, μ represents indicator variables for the years and v denotes the error term. The index i represents the country level and the index t the temporal level. The sample is unbalanced and the intervals are every 5 years, from 1965 through to 2000, so we have 7 different periods.

Random-effects estimation assumes that the relations between inputs and outputs are distributed randomly between countries and between years. Now, it is highly probable that unobserved effects of countries are present in the estimations and interfere with the β. If such is the case, then the relations found in a random-effects estimation are potentially biased. To correct this bias, we then perform a fixed-effects estimation. Here, the estimator is that of the panel OLS with dummy variables δ for each country *i*, and dummy variables μ pour for each year *t*:

$$q_{it} = \alpha_{it} + \beta_1 f_{it-1} + \beta_2 s_{it-1} + \mu_t + \delta_i + v_{it} \tag{2}$$

There are three main reasons why the relation described above might be biased when the fixed effects are taken into account. Firstly, there may be no direct relation between an educational *investment* or a *form of organization* of education in a country and the school performance in that same country. In this case, the relations found with the fixed-effects estimator can be biased in many different ways and indicate significant relations where there are none. Another possible reason comes from measurement errors in the estimation of the quality of education. If, for example, the measurement errors are greater for a specific year, the fixed-effects estimator tends to bias the specification even further. Another likely reason arises out of the problem of endogeneity. For example, if a country can improve its education quality by reducing the size of classes, the opposite relation is equally possible: it can reduce class size because its population has access to high-quality education. The same relation of reciprocal causality may exist for the other variables. Because of this bias of causality, the fixed-effects estimator itself may be biased. To correct all these biases, we use the generalized method-of-moments estimator, where the endogenous variables are instrumented by the values of the lags of the same variables. In this case, we estimate the following equation:

$$\Delta q_{it} = \beta_1 \Delta f_{it-1} + \beta_2 \Delta s_{it-1} + \Delta \mu_t + \Delta u_{it} \tag{3}$$

As can be seen, we regress the variation of output with the variation of each of the inputs, so as to purge the whole estimation of fixed effects. In this precise case, it is no longer the *level* of an input that determines the *level* of an output, but the *variation* of the former that determines the *variation* in the latter. The estimator we use consists in adding instruments in levels to the classic instruments, so as to form a *system* of the generalized method-of-moments. To correct these biases, we use another regressor, that of the generalized method of moments (the GMM system), with an application by Blundell and Bond (1998). This regression is performed on a dynamic panel model and uses the levels and lags of endogenous variables as instruments. While Arellano and Bond (1991) use the first-difference estimator to avoid the correlation between the lagged values of the dependent variable and the fixed effects included in the term of error, Arellano and Bover (1995) again include the equations expressed in levels, in addition to the lagged values of the first differences, to avoid being confronted with the problem of the validity of the instruments, as highlighted by Staiger and Stock (1997). In addition, they show that the inclusion of equations in levels considerably increases the accuracy of the estimators, particularly when the auto-correlation of the dependent variable is strong.

However, the total number of instruments sometimes becomes too high in relation to the observations, sometimes even higher than the number of countries included in the panel. Because of the new level constraints introduced, this problem arises more often with the Blundell and Bond estimator (1998) that we use for our regressions. The improvement made by Roodman (2006) to this estimator in the Stata© software enables us to use an original method to limit the problem of the number of instruments. The "collapse" option in Stata can be used to restrict the number of instruments by only considering some of the lagged variables instead of all of them. In our analysis, this option is only used when the number of observations is lower than 200, in other words when the qualitative indicators of human capital are used to measure school performance and sub-samples are used. With Blundell and Bond's estimator (1998), we have a choice between one-step and two-step estimation. The simulations carried out by Arellano and Bond (1991) suggest that two-step estimation can improve the accuracy of estimated coefficients and considerably increase the quality of the estimation in the event of heteroskedasticity, but the standard errors tend to be systematically undervalued. For this reason, we have chosen not to use the two-step version.

It is important to note that we make use of proxy variables, notably in order to take family factors into account. As McCallum (1972) demonstrates, when there are no errors in the measurement of either the proxy variables or the other inputs, it is preferable to include such variables in the specification. Nevertheless, we are still confronted with the problem of whether the use of such proxies might not add even more bias to the model. For example, we use the variable of educational expenditure per student as a proxy to offset the lack of other educational inputs, assuming that it can explain all the educational inputs. But the inclusion of such a proxy can induce an even greater estimation bias (Wolpin, 1995, 1997; Todd and Wolpin, 2003). Todd and Wolpin (2003) show that the use of proxies in an educational production function can complicate the interpretation of coefficients. They consider the example of a model relating performance to an input such as class size. To avoid having to leave out the missing variables for other inputs, a researcher might include a variable such as the level of educational expenditure per student. However, it is perfectly possible that schools with the same level of spending per student, but with smaller-sized classes, spend less on other, unobservable variables (such as employing less experienced teachers). Consequently, the effect of class size on school performance, with a given level of educational spending per student, is measured with the hypothesis of constancy in the unobservable input factors. If class size and unobservable inputs are not correlated, then the bias due to omitted variables is null in the model without proxy. By including the proxy of educational expenditure in the regression, we assume that the variations in class size are merged with the variations in unobserved inputs. In this sense, the inclusion of proxies can exacerbate the biases. Alternatively, proxies such as income per capita or educational expenditure can be used to verify the importance of biases due to omitted variables. These biases exist if the inclusion of these proxies affects school performance, with the other inputs remaining unchanged. If it turns out that the effects of included inputs change considerably when the proxies are included in the regression, Wolpin (1995) shows that the researcher cannot know which of the estimations is the least biased. For these reasons, we estimate each regression again, using one sole input each time, but including the variable of the educational level of adults to control for family effects. As we use a fixed-effects estimator and the generalized methods-of-moment estimator of Blundell and Bond (1998), the fixed effects are purged, which theoretically limits the biases due to omitted variables. Consequently, with such estimators, the inclusion of only part of the variables in the regression should not lead to an overestimation of their impact on educational output.

3.3. Results of the estimations

In Table 3, we estimate the educational production function with random effects using the results of mathematics tests at secondary level and the net enrollment ratio at secondary level as output indicators (equation 1). To capture the variations due uniquely to the temporal dimension, we introduce indicator variables for each year considered. Fisher's test of global significance of the indicators for each year shows the importance of incorporating them into the estimation. Even when their significance is rejected at the 10% level, the value of the other coefficients is not changed. In addition, the standard deviations are corrected by the cluster method and are robust to heteroskedasticity.

Column (1) shows the analysis carried out on the basis of the first spending indicator, i.e. educational expenditure per student at secondary level as a percentage of GDP per capita. Only the variable of the educational level of adults is positive and significant. Whatever other inputs are included, their coefficients are never significant. The relations are different with the use of net enrolment ratio (NER) as output indicator (columns 7 to 12). Likewise, the educational level of adults has a positive and significant relation to the enrollment rate. Educational expenditure is either negatively correlated (column 7), or not significant (column 8). Teachers' pay is negatively correlated with both of the outputs used, but only significantly with the enrollment rate. In addition, the same negative relation exists for class size and for the repetition rates. Only the coefficients in the estimation with the enrollment rate are significant. Lastly, despite a negative coefficient, educational inequalities do not appear to have an impact on school performance, whichever output is used.

These results may be biased, because our estimations consider that the variations in the different variables between and within countries are distributed randomly. Moreover it is probable that omitted variables exist which influence both inputs and outputs, thus leading to estimation biases. Table 5 presents the fixed-effects estimations, where we include the indicator variables for each country. When the fixed effects are taken into account, the inputs no longer appear to have any effect on educational performance, whatever the nature of this latter. Even the variable of the educational level of adults is only significant for 3 estimations out of a total of 12 (columns 7, 9 and 10), which raises doubts about its actual effect on school performance. When the test scores are used, no variable is significant. The samples are relatively small and in general we only have three observations for each country considered. Still, if the sample size was the main problem, we should obtain more significant results when we use net enrollment rates. But this is not the case. Only educational inequalities appear to have a negative influence on the enrollment rate at secondary level. A reduction of one standard deviation in the level of educational inequalities induces an increase of about 11 percent. This effect is very powerful, but the causal relation between enrollment rate and the level of educational inequalities is not controlled for by the fixed-effects method of regression. To correct these biases, we use the generalized method-of-moments estimator.

The results of the estimation using the GMM system are presented in Table 6. As in the previous estimations, the estimations are performed with a limited number of independent variables, to avoid bias in the estimated coefficients. There is no possible bias due to the presence of omitted variables, because the estimation is made on the rates of variation, which theoretically eliminates the unobservable characteristics. In columns 1 to 6, we use the student test scores as output, while columns 7 to 12 show the results of estimations using the enrollment rate. When we use the test scores, only the variable relating to parents' income is significant: an increase of one standard deviation in the educational level of adults (i.e. about 2.7 years in 1995) induces an increase of about 6 percent in student scores, representing more than double the impact when the regression is performed with random effects ($2.72 \times 2.22 = 6.04$). When the variable of educational expenditure is introduced, it is still not positive and significant. Even more importantly, its impact appears to be negative and significant for the enrollment rate. The other indicator of educational expenditure also produces negative, but not significant coefficients. This strengthens our idea of the lack of relation between the level of spending on education and the quality of education. None of the other inputs has a direct influence on the quality of education when the test scores are used as output. With the enrollment rate as output, teachers' pay even has a negative and significant effect on it. Educational inequalities also have a negative, significant impact on the enrollment rate. Consequently, when the estimation biases are controlled for, the educational production function loses its relevance. At most, the educational level of adults explains the level of school performance.

It should be noted that both educational performance and the structure of educational systems differ strongly between different countries and different economic levels. In this case, it is possible that our estimations are biased because they include very diverse countries, notably both developed and developing countries. Although Blundell and Bond's estimator (1998) is usually operated with fixed effects, we require each country to follow one sole production function. To verify this hypothesis, we estimate the above specifications once again, distinguishing between the economic levels of the countries. As our sample is fairly small, we have chosen to distinguish between OECD countries and non-OECD countries. The results presented in Table 7 show that the difference in the educational production function between countries of different economic levels is not proven. Only four variables are significant. It is important to note that the samples are very small, and this may reduce the significance of the coefficients. Notwithstanding, it is surprising to observe that the educational level of adults seems no longer to have an effect on test scores when the distinction is made between countries of different economic levels. Only two estimations for the non-OECD countries produce a positive and significant impact of the educational level of adults. Educational expenditure has no effect on test scores, whatever the economic level of the countries considered. In an unremarkable way, teachers' pay has a negative and significant impact on the quality of education for the developing countries (column 9). The increase of a standard deviation of teachers' pay (i.e. a rise of 241% in 1995 for non-OECD countries) induces a fall of 11 percent in the quality of education. This effect is about five times higher than it is with the random-effects estimator and concerns all the countries in the sample (column 3 in Table 7), but remains fairly weak considering that this increase in pay represents a multiplication by more than 3. The size of classes has a positive effect for OECD countries and negative for developing countries. However, the effect is only significant for the former group. In any event, we observe no negative and significant effect, whatever the economic level of the countries considered. In addition, the repetition rates have a negative and significant impact for the developing countries. Here, the effect of repeated years is very strong: a reduction of one standard deviation (i.e. 7.3 in 1995 for the non-OECD countries) induces an increase of 6 percent in the test scores. We repeat the same procedure with the enrollment rate as the educational output (Table 8). The educational level of adults retains its positive and significant effect, whatever the economic level of the countries. On average, the impact of the educational level of adults on the enrollment rate is stronger for developing countries than for OECD countries. In this difference, we can read a process of educational convergence between countries with different economic levels. The impact of educational expenditure is unconvincing, to say the least. Admittedly, its effect on the enrollment rate is positive and significant for OECD countries, but only at a level of significance of 10%. When educational expenditure as a percentage of GNP is used as an alternative variable, the relation disapears. The effects are equally contrasting for the developing countries, where only the use of the second indicator produces a negative and significant relation. One quite surprising result is the positive effect of repeated years on the enrollment rate in OECD countries. But this appears to be of lower amplitude. These results underline the need to distinguish the economic level of the countries clearly, which leads us to reject the existence of the educational production function.

4. Conclusion

The objective of this paper has been to determine the extent to which, within an educational system, school resource factors have an impact on school quality. For this purpose, we have estimated an educational production function. As it would for a firm, this function relates inputs to an output. In this case, we have chosen two outputs. The first concerns student scores in international achievement tests. It is reasonable to consider that the performance of an educational system can be measured through student scores in standardized tests of skills such as mathematics, science and reading. However, given the limited nature of data on international tests, we have also used net enrollment rate at the secondary level. By choosing such an indicator as an alternative to the international tests, we have favored the quantitative dimension.

Each country seeks to achieve the best performance for its educational system, at the lowest possible cost. As we have seen over the course of this paper, there is no established relation between resource factors and the performance of an educational system. With the growing globalization of economic activities, governments are more and more preoccupied with the performances of their educational systems. It appears important to search for specific educational policies that can improve them. But increasing school resources have not established effects on school quality at the macroeconomic level: educational systems are so complex, and there are so many factors at work that it remains very difficult to search for the sources of the quality of education.

What are the main reasons conducting to a lack of relationship between school resources and the quality of education? We can think that there can be two main hypotheses. Firstly, as we suggested it in the section 2.3., our data can suffer for measurement bias. Obviously, we computed a new database, using many different surveys. Despite the meticulous work done for making these data comparable, it could be possible that our analysis of difference-in-difference may suffer for measurement error, as it is often the case in growth econometrics estimations. However, it will never possible to obtain a precise measure of education quality, since this is a multidimensional variable of the education system. The second reason of the lack of relationship is perhaps an established lack of effect from school resources to education quality. Why in a given country, due to an increase of school resources, will education quality systematically improve?

Still, it remains fundamentally important for a country to evaluate the quality of its educational system. International surveys surely have a promising future. If existing databases of standardised skills tests remain limited in the number of observations, it may be possible to verify the existence of an educational production function in the coming years, thanks to the new surveys that are being conducted now or will be conducted in the future.

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Table 1 **- Sources of data used**

Indicator	Abbreviation	Period	Source
Quality of education	QIHC	1965-2002	Altinok and Murseli (2007)
Net enrollment rate in secondary education	NERSEC	1970-2005	UNESCO-Institute for Statistics
Parents' education: average number of years schooling for adults aged over 25	ADEDU	1960-2005	Barro and Lee (2001), UNESCO-Institute for Statistics
Govt. spending per student at primary level as % of GDP per capita	SHPUPP	1960-2002	Barro and Lee (1996), UNESCO-Institute for Statistics
Govt. spending per student at secondary level as % of GDP per capita	SHPUPS	1960-2002	Barro and Lee (1996), UNESCO-Institute for Statistics
Govt. spending at primary level as % of GNP	EXPGNP	1970-2005	UNESCO-Institute for Statistics
Teachers' pay at primary level as % of GDP per capita	SHSALP	1960-2002	Barro and Lee (1996), UNESCO-Institute for Statistics
Class size at primary level	TEAPRI	1960-2005	Barro and Lee (1996), UNESCO-Institute for Statistics
Class size at secondary level	TEASEC	1960-2005	Barro and Lee (1996), UNESCO-Institute for Statistics
Repetition rates at primary level	REPPRI	1970-2005	Barro and Lee (1996), UNESCO-Institute for Statistics
Repetition rates at secondary level	REPSEC	1970-2005	Barro and Lee (1996), UNESCO-Institute for Statistics
Indicators of educational inequalities	INEDU	1960-2000	Altinok (2007)
Expected number of years in education	EXPEN	1970-2005	UNESCO-Institute for Statistics

Table 2 – **Student achievement tests used**

Year	*Abbreviation*	*Field*	*Countries*	*Age of students*
1964	IEA	Mathematics	13	13, Fin sec.
1970-72	IEA	Science Reading	19 15	10,14, Fin sec. 10,14, Fin sec.
1982-83	IEA	Mathematics	20	13, Fin sec.
1984	IEA	Science	24	10,14, Fin sec.
1988	IAEP	Mathematics Science	6 6	13 13
1991	IEA	Reading	31	9,14
1990-91	IAEP	Mathematics Science	20 20	9,13 9,13
1993-98	IEA	Mathematics Science	41 41	9,13, Fin sec. 9,13, Fin sec.
1992-97	UNESCO-MLA	Mathematics Science Reading	13 11 11	10 10 10
1997	UNESCO-LLECE	Mathematics Reading	11 11	10 10
1999	UNESCO-SACMEQ	Reading	7	10
1999	IEA	Mathematics Science	38 38	14 14
1995-2005	CONFEMEN-PASEC	Mathematics Reading	11 11	9,10 9,10
2000	OECD-PISA	Mathematics Science Reading	43 43 43	15 15 15
2001	IEA	Reading	35	9,10
2002	UNESCO-SACMEQ	Mathematics Reading	14 13	10 10
2003	IEA	Mathematics Science	26,48 26,48	10,14 10,14
2003	OECD-PISA	Mathematics Science Reading	41 41 41	15 15 15

Note: Fin sec. denotes the final year of secondary school. Abbreviations: IAEP (International Assessment of Educational Progress), IEA (International Association of the Evaluation of Educational Achievement), TIMSS (Third International Mathematics and Science Study), PIRLS (Progress in International Reading Literacy Study), PISA (Programme for International Student Assessment), UNESCO (United Nations Educational, Scientific and Cultural Organization), LLECE (Latin American Laboratory for Assessment of the Quality of Education), CONFEMEN (Conference of Ministers of Education in countries sharing the French language), PASEC (Programme of Analysis of the CONFEMEN), SACMEQ (Southern and Eastern Africa Consortium for Monitoring Educational Quality), MLA (Monitoring Learning Achievement).

Table 3 - **Descriptive statistics**

Variable		*Mean*	*Standard deviation*	*Min*	*Max*	*Obs*	*Obs*
QIHC	Overall	51.58	10.06	18.75	78.31	N	244
	Between		9.37	18.75	70.99	n	106
	Within		5.52	24.53	64.83	T	2.30
NERSEC	Overall	54.20	29.04	0.90	100	N	577
	Between		27.62	2.30	97.5	n	158
	Within		11.93	12.20	101.07	T	3.65
LNGDP	Overall	8.19	1.07	5.77	10.69	N	1082
	Between		0.99	6.25	10.03	n	146
	Within		0.32	6.87	9.35	T	7.41
ADEDU	Overall	4.60	2.83	0.04	12.25	N	1048
	Between		2.48	0.41	10.86	n	169
	Within		1.05	0.85	8.15	T	6.20
TEAPRI	Overall	31.72	12.95	6.10	95.3	N	1296
	Between		11.61	13.40	73.07	n	176
	Within		5.93	10.89	56.77	T	7.36
TEASEC	Overall	19.36	7.12	6	64	N	1149
	Between		6.01	8	45.5	n	176
	Within		4.27	-2.21	45.79	T	6.53
SHPUPP	Overall	14.22	9.19	0.95	77.80	N	845
	Between		9.43	2.27	49.76	n	156
	Within		5.49	-10.39	54.64	T	5.42
SHPUPS	Overall	39.08	60.86	2.1	693.8	N	816
	Between		46.09	4.83	275.83	n	154
	Within		40.52	-119.12	460.91	T	5.30
EXPGNP	Overall	4.40	1.97	0	13.3	N	831
	Between		1.87	0.78	13.3	n	174
	Within		1.04	-0.45	9.33	T	4.78
SHSALP	Overall	354.88	278.40	40	2684	N	714
	Between		232.26	40	1396.25	n	145
	Within		153.71	-431.38	1642.63	T	4.92
REPPRI	Overall	10.36	9.28	0	47.5	N	996
	Between		8.63	0	34.15	n	174
	Within		3.50	-4.83	25.76	T	5.72
REPSEC	Overall	9.54	8.24	0	46	N	819
	Between		7.15	0	31.2	n	156
	Within		3.95	-8.06	28.47	T	5.25
INEDU	Overall	44.01	25.63	4.41	98.97	N	925
	Between		24.62	7.13	92.27	n	109
	Within		7.75	16.93	67.42	T	8.49

Note: For the abbreviations, see Table 1.

Table 4 – **Random-effects estimation**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dependent variable	Quality of education in mathematics at secondary level						Net enrollment rate at secondary level					
Education of adults $_{t-1}$	1.101* (0.367)	1.730* (0.461)	0.831‡ (0.473)	1.486* (0.453)	1.710* (0.532)	1.024‡ (0.623)	7.902* (0.463)	7.991* (0.531)	7.846* (0.589)	7.856* (0.536)	7.856* (0.536)	8.591* (0.511)
Educational spending$^{(1)}$ $_{t-1}$	0.037 (0.092)						-0.122* (0.049)					
Educational spending $^{(2)}$ $_{t-1}$		-0.366 (0.493)						0.936 (0.740)				
Teachers' pay $_{t-1}$			-0.009 (0.012)						-0.018† (0.008)			
Class size $_{t-1}$				-0.167 (0.206)						-0.410† (0.172)		
Repetition rates $_{t-1}$					-0.065 (0.165)						-0.410† (0.172)	
Educational inequalities $_{t-1}$						-0.102 (0.109)						-0.031 (0.148)
F Test for time dummies	[0.00]	[0.00]	[0.01]	[0.00]	[0.04]	[0.00]	[0.00]	[0.01]	[0.02]	[0.00]	[0.00]	[0.01]
Observations	156	148	119	143	117	161	373	388	308	420	420	352
Country	58	63	41	60	55	54	117	126	112	133	133	121
R^2	0.47	0.31	0.49	0.47	0.48	0.44	0.75	0.71	0.76	0.73	0.73	0.69

Levels of significance: *1%. †5%. ‡10%. The numbers between brackets represent standard errors.
(1) Educational spending per student at secondary level as percentage of GDP per capita.
(2) Educational spending as percentage of GNP.

Table 5 – **Fixed-effects estimation**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dependent variable	Quality of education in mathematics at secondary level							Net enrollment rate at secondary level				
Education of adults $_{t-1}$	1.776 (1.284)	0.288 (1.111)	1.931 (1.399)	0.637 (1.350)	2.194 (1.721)	1.378 (1.244)	3.129† (1.361)	1.279 (1.514)	3.105‡ (1.850)	2.564‡ (1.369)	1.910 (1.822)	1.261 (1.246)
Educational spending[(1)] $_{t-1}$	0.002 (0.115)						-0.052 (0.066)					
Educational spending [(2)] $_{t-1}$		0.967 (0.655)						0.742 (0.815)				
Teachers' pay $_{t-1}$			0.007 (0.010)						0.008 (0.007)			
Class size $_{t-1}$				-0.137 (0.327)						0.191 (0.201)		
Repetition rates $_{t-1}$					0.038 (0.290)						0.176 (0.323)	
Educational inequalities $_{t-1}$						0.166 (0.200)						-0.485* (0.146)
F Test for time dummies	[0.53]	[0.69]	[0.33]	[0.82]	[0.24]	[0.00]	[0.00]	[0.00]	[0.01]	[0.00]	[0.00]	[0.00]
Observations	156	148	119	143	117	161	373	388	308	420	352	416
Countries	58	63	41	60	55	54	117	126	112	133	121	96
R^2	0.91	0.31	0.91	0.47	0.94	0.92	0.96	0.95	0.96	0.73	0.94	0.95

Levels of significance: *1%. †5%. ‡10%. The numbers between brackets represent the standard errors. The independent variables are lagged for a period of 5 years.

(1) Educational spending per student at secondary level as percentage of GDP per capita.

(2) Educational spending as percentage of GNP.

Table 6 - **Estimation with GMM system**

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*	*(10)*	*(11)*	*(12)*
Dependent variable	Quality of education in mathematics at secondary level						Net enrollment rate at secondary level					
Education of adults $_{t-1}$	2.222*	2.053†	1.932‡	2.775*	1.735‡	2.991†	7.632*	7.210*	8.932*	9.044*	8.742*	3.398†
	(0.854)	(0.857)	(1.092)	(0.935)	(0.936)	(1.218)	(0.752)	(0.885)	(0.856)	(0.866)	(0.740)	(1.485)
Educational spending$^{(1)}$ $_{t-1}$	-0.036						-0.118†					
	(0.167)						(0.050)					
Educational spending $^{(2)}$ $_{t-1}$		-0.495						-1.444				
		(1.154)						(1.040)				
Teachers' pay $_{t-1}$			-0.011						-0.022*			
			(0.016)						(0.009)			
Class size $_{t-1}$				-0.122						-0.226		
				(0.370)						(0.220)		
Repetition rates $_{t-1}$					0.181						0.064	
					(0.181)						(0.181)	
Educational inequalities $_{t-1}$						0.232						-0.690*
						(0.252)						(0.223)
F Test for time dummies	[0.00]	[0.01]	[0.00]	[0.00]	[0.04]	[0.01]	[0.00]	[0.01]	[0.07]	[0.00]	[0.04]	[0.00]
Hansen's test	[0.32]	[0.22]	[0.36]	[0.18]	[0.47]	[0.24]	[0.80]	[0.41]	[0.96]	[0.24]	[0.29]	[0.54]
AR(2) test	[0.23]	[0.20]	[0.19]	[0.76]	[0.34]	[0.74]	[0.72]	[0.76]	[0.23]	[0.26]	[0.25]	[0.21]
Observations	156	148	119	143	117	161	373	388	308	420	352	416
Countries	58	63	41	60	55	54	117	126	112	133	94	96

Levels of significance: *1%. †5%. ‡10%. The numbers between brackets represent the standard errors. The independent variables are lagged for a period of 5 years.
(1) Educational spending per student at secondary level as percentage of GDP per capita.
(2) Educational spending as percentage of GNP.

Table 7 - **Estimation with test scores, sub-samples**

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*	*(10)*	*(11)*	*(12)*
Dependent variable	Quality of education in mathematics at secondary level											
Sample	OECD countries						Non-OECD countries					
Education of adults $_{t-1}$	1.259 (1.064)	-0.099 (0.980)	1.091 (0.855)	1.052 (0.762)	-0.965 (1.655)	0.433 (1.228)	1.668 (1.232)	1.783† (0.871)	1.204 (1.363)	0.864 (1.278)	1.501† (0.752)	2.651 (1.849)
Educational spending[(1)] $_{t-1}$	0.031 (0.149)						0.085 (0.220)					
Educational spending [(2)] $_{t-1}$		0.127 (0.923)						-0.362 (1.080)				
Teachers' pay $_{t-1}$			-0.003 (0.018)						-0.055‡ (0.031)			
Class size $_{t-1}$				0.407‡ (0.211)						-0.472 (0.426)		
Repetition rates $_{t-1}$					0.419 (0.397)						-0.837‡ (0.493)	
Educational inequalities $_{t-1}$						-0.072 (0.198)						0.048 (0.364)
F Test for time dummies	[0.11]	[0.03]	[0.12]	[0.01]	[0.03]	[0.07]	[0.00]	[0.09]	[0.00]	[0.00]	[0.00]	[0.01]
Hansen's test	[0.57]	[0.35]	[0.27]	[0.40]	[0.83]	[0.38]	[0.34]	[0.78]	[0.99]	[0.64]	[0.62]	[0.52]
AR(2) Test	[0.87]	[0.79]	[0.79]	[0.68]	[0.57]	[0.67]	[0.30]	[0.79]	-	[0.67]	[0.60]	[0.76]
Observations	106	91	90	88	67	111	50	57	29	55	50	50
Countries	22	28	22	28	24	28	29	35	16	32	31	26

Levels of significance: *1%. †5%. ‡10%. The numbers between brackets represent the standard errors. The independent variables are lagged for a period of 5 years.

(1) Educational spending per student at secondary level as percentage of GDP per capita.

(2) Educational spending as percentage of GNP.

Table 8 - **Estimation with net enrollment rate, sub-samples**

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*	*(10)*	*(11)*	*(12)*
	System GMM											
Sample	OECD countries							Non-OECD countries				
Education of adults $_{t-1}$	4.547* (1.190)	1.726‡ (0.967)	6.154* (1.469)	5.343* (1.388)	3.009† (1.313)	1.848 (2.034)	6.205* (2.513)	8.516* (2.552)	6.145* (2.161)	8.051* (2.134)	5.771† (2.902)	8.080* (2.388)
Educational spending$^{(1)}$ $_{t-1}$	0.431‡ (0.218)						-0.093 (0.063)					
Educational spending $^{(2)}$ $_{t-1}$		0.308 (1.382)						-1.807‡ (1.114)				
Teachers' pay $_{t-1}$			-0.015 (0.016)						-0.007 (0.016)			
Class size $_{t-1}$				-0.431 (0.614)						-0.261 (0.266)		
Repetition rates $_{t-1}$					0.245* (0.061)						0.594 (0.674)	
Educational inequalities $_{t-1}$						-0.421 (0.364)						-0.464 (0.339)
F Test for time dummies	[0.00]	[0.00]	[0.07]	[0.00]	[0.00]	[0.00]	[0.00]	[0.57]	[0.05]	[0.10]	[0.05]	[0.15]
Hansen's test	[0.31]	[0.48]	[0.18]	[0.60]	[0.63]	[0.31]	[0.16]	[0.61]	[0.25]	[0.16]	[0.38]	[0.82]
AR(2) Test	[0.18]	[0.47]	[0.12]	[0.96]	[0.76]	[0.47]	[0.41]	[0.92]	[0.23]	[0.21]	[0.55]	[0.18]
Observations	146	133	126	129	89	158	227	255	182	291	263	258
Countries	27	28	27	28	26	27	26	98	85	105	95	69

Levels of significance: *1%. †5%. ‡10%. The numbers between brackets represent the standard errors. The independent variables are lagged for a period of 5 years.
(1) Educational spending per student at secondary level as percentage of GDP per capita.
(2) Educational spending as percentage of GNP.